

# Bivariate / Joint Probability Distributions – Statistics – Prof. Richard B. Goldstein

**Discrete**  $f(x, y) = P(X = x, Y = y) \geq 0 \quad \forall x, y$   
 $\sum_x \sum_y f(x, y) = 1 \quad P[(X, Y) \in A] = \sum_A \sum f(x, y)$

**Continuous**  $f(x, y) \geq 0 \quad \forall x, y$   
 $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy = 1 \quad P[(X, Y) \in A] = \iint_A f(x, y) dx dy$

## Marginal Distributions

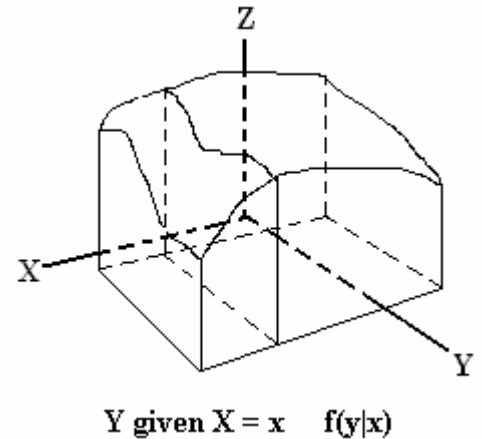
**Discrete:**  $g(x) = \sum_y f(x, y) \qquad h(y) = \sum_x f(x, y)$

**Continuous:**  $g(x) = \int_{-\infty}^{\infty} f(x, y) dy \qquad h(y) = \int_{-\infty}^{\infty} f(x, y) dx$

## Conditional Distributions

**Y given X = x**  $f(y | x) = \frac{f(x, y)}{g(x)}, \quad g(x) > 0$

**X given Y = y**  $f(x | y) = \frac{f(x, y)}{h(y)}, \quad h(y) > 0$



## Statistically Independent

independent  $\Leftrightarrow f(x, y) = g(x)h(y) \quad \forall x, y$

## Expected Values and Variances (similar formulas for discrete case)

$E[X] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xf(x, y) dx dy \qquad E[Y] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} yf(x, y) dx dy$

$E[X^2] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^2 f(x, y) dx dy \qquad \text{Var}[X] = E[X^2] - (E[X])^2$

$E[XY] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xyf(x, y) dx dy \qquad \text{Co var}[X, Y] = E[XY] - E[X]E[Y]$

$E[Y | X = x] = \int_{-\infty}^{\infty} yf(y | x) dy \qquad E[X | Y = y] = \int_{-\infty}^{\infty} xf(x | y) dy$